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Retraction

Retracted: Study on Aircraft Cockpit Function Based on Neural Network

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Z. Xu and Y. Sun, "Study on Aircraft Cockpit Function Based on Neural Network," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 7794982, 8 pages, 2022.

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Research Article

Study on Aircraft Cockpit Function Based on Neural Network

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With the rapid development of numerous airlines, various trend designs have been implemented to develop cockpit interiors for pilots. When communicating with most pilots, they express their emotional feelings about the cockpit. The performance-enhanced cockpit provides the pilot with a better emotional experience, further enhancing the comfort and pleasure of driving. Therefore, it is necessary to provide a cockpit with good performance. Therefore, this paper proposes a novel Neural Network-based Balanced Optimization Algorithm (NN-EOA) for cockpit emotion recognition. The proposed NN-EOA technique simulates quantitative computation with high accuracy and minimizes the error rate during evaluation. Here, images of the interior cockpit design were assessed on four emotional terms, namely, user-friendly (interactive), precise (precise), traditional (traditional), and neat (tidy). Finally, experimental results are performed on various parameters, namely, the mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) for various techniques. From the experimental evaluations, it can be seen that the proposed NN-EOA provides high agreement rates in the experimental group with the smallest MAE, MAPE, and RMSE.

1. Introduction

The cockpit was controlled by a pilot and copilot. The two main responsibilities of the cockpit are to present a very good obliquity and to create control techniques approachable to them. Aircrafts are made by the same principle as a vehicle. According to the records of recent years, from aircraft accidents, ensure the connection among good cooperation in the cockpit and impregnability [1]. The US Airways aircraft landed on the Hudson River because of the danger, which is being the best example of excellent group work. That group work contains earlier decision-making skills and cooperation among the cockpit group members and cabin group members in the main danger [2]. Through the use of team resource management goals and to accept the group work orderly, in the cockpit and cabin, all the resources are available, like crew, aircraft, support groups, air transportation control, or mechanics developments [3]. Identifying essential resources for powerful and secure cooperation in the cockpit as well as making them into guiding schedule is the research in recent years [2]. With the support of other aircrafts' sketch experience, skillful boundaries and maintained essential feature command systems are growing continuously; with this growth, a diversified method flow has been expressed [4]. The importance of this method is to frame the cockpit's center. The interaction with pilots expresses the sharing about the structure of the cockpit. A cockpit has to be framed for a model, according to the comforts of the pilot. Through the technical skill of aircraft cockpit, a good comfortable experience may develop like the happiness in driving [5]. Saberi-Movahed et al. [6] conducted a high-dimensional reduction of blood biomarker space in a cohort of COVID-19 patients based on matrix factor-mediated feature selection, and the results showed that arterial blood gas oxygen saturation and C-reactive protein (CRP) were the most important clinical biomarkers for poor prognosis in these patients. Najafzadeh et al. [7] used group data processing (GMDH) to predict the 3 d freespan expansion rate around the pipe induced by waves. The performance of GMDH-GEP model was compared with that of artificial neural network (ANN), GEP, GMDH, and traditional regression model based on equation. Sensitivity analysis and parameterization studies were performed to perceive the effects of different input parameters on the three-dimensional scour rate. Najafzadeh et al. [8] applied a machine learning (ML) model to implement an equation for predicting the propagation rate of scour around a pipe due to current flow. Using the explicit equation generated by the ML model, they verified the agreement of the proposed method with experimental observations. The results show that the equations given by the ML model provide reliable and physically consistent predictions of search propagation rates in comparison with washout tests.

The fundamental performance may be a satisfying cockpit technology. Recently, the aircraft cockpit decision is generally concentrated on the sufficiency evaluation [9]. There are comparative entire theories and structures maintained, created, and grown-up many computer programmes and hardware tools enduring research and training for this purpose. Particularly, the building research institute airbus, the ensemble's inclusive evaluating structure for the human-machine surrounding A320 full-motion simulator, has been expressed at a great distance [10]. Various researchers express the neural network (NN) is the right method for emotional analysis and linguistic consideration. The bendable and nonlinear active mapping methods are derived from the neural network method [11]. Additionally, the use of neural networks to acquire information about theoretical characteristics may avoid hand operation distillation of feature remoteness and conscious functions. With the growth in technology of Artificial Intelligence (AI), researchers utilized neural network (NN) methods, through various methods like sound, face-oriented verbalization, brain signal, and visibility methods to judge understanding [12]. The emotional representation of the aircraft cockpit center method is considered through the characteristic imagery dimensions. Subjective and objective evaluation is the two divisions in the aircraft cockpit. Participants' experience is considered a subjective evaluation. It must be ensured that the acquired findings are frequently deeply moved by various like participants' experience and professional stage. Eye trackers believed objective evaluation method. Pressure analysis measurement method and electromyography record physical features of the human body while utilizing [13]. A neural network is an order of algorithms that are struggling to identify the fundamental connection in a dataset through a procedure that imitates the path the human brain functions. In this function, neural network (NN) refers to methods of neurons, either natural or artificial [14–16]. Thus, applying the conventional method is not the present standardized outcome to the aircraft cockpit function, but utilizing a neural network algorithm expresses perfect results. This paper proposes a novel neural network-based equilibrium optimization algorithm (NN-EOA) for cockpit emotion recognition. The important contributions of the paper are described as follows.

(i) To propose a novel artificial neural network based equilibrium optimization algorithm (NN-EOA) for recognizing the emotions of the cockpits

(ii) To simulate the quantitative computation with high accuracy thereby minimizing the error rate

(iii) To evaluate four emotional terminologies, namely, user-friendly (interactive), exact (precise), conventional (traditional), and tidy (neat), for effective designing of cockpit

The remainder of the paper is structured in the following manner. In Section 2, the past literature work based on cockpit emotion recognition is presented. The proposed methodology is discussed in Section 3. The results and discussions are presented in Section 4. Finally, Section 5 concludes the article.

2. Literature Survey

Zhou et al. [17] proposed a hybrid deep neural network (HDNN) which is based on a multitime window convolutional neural network-bidirectional long short memory (CNN-BiLSTM) for identifying the hazard of Auxiliary Power Unit for civil aircraft. To obtain initial identification results, multiple CNN-BiLSTM basis models were utilized by HDNN and a totally connected NN integrates the final identification result of hazard information gather from the initial identification. It is shown that the identification accuracy of HDNN is the best and the hazard identification accuracy can be improved by the HDNN which was proposed. Pytka et al. [18] presented the development of the IMUMETER sensor which was designed for measuring the aircraft's ground performance and also to study the aircraft movement's dynamics. To develop a sensor for the measurement of airplane motion, airfield performance, etc. was the study's motivation. Based on the artificial neural network's model the IMUMETER sensor was designed. The paper describes the convolution neural network development and using the neural network model the test airplane's ground distance while landing was calculated. It was shown in the result that the distance measurement accuracy of the smartphone-based version of IMUMETER was insufficient. The conclusion was that as the next step of the project, in the improved version of IMUMETER, a DGPS-based hardware algorithm would be used.

Muhammad et al. [19] presented an adaptive artificial neural network (ANN) observer for detecting the aircraft's fault. Based on a NN with a modified weight tuning algorithm, fault control is also proposed. It was found that the proposed strategy's tracking and stability performance is better when compared with conventional strategy, and in the presence of failure and faults, it shows high robustness. Kumar et al. [20] evaluated the efficiency of a Levenberg Marquardt Algorithm for cockpit control in an unmanned aircraft. Depending upon the prior cases of the Levenberg Marquardt Algorithm, the neural network's overall performance was calculated. The highest accuracy of the neural network was achieved by the Levenberg Marquardt algorithm. It was found that the identification accuracy of the Levenberg Marquardt Algorithm was the best.

Yin et al. [21] analyzed the aircraft cabin environment satisfactory level of VOCs during flights and examined the detection rates, exposure concentrations, and health risk assessments which are the key volatile organic compound identification in aircraft cabins. Exploring the forecast of TVOC on a flight neural network algorithm was introduced. The study recommended the hierarchical design of pollutant concentration for the aircraft cabin. Beulen et al. [22] addressed the problem of dynamic evaluating flight requests. To assess each flight request, a neural network classification was proposed in the paper and a dynamic rostering framework was developed to test and train the neural network algorithm. The framework combined a mixed-integer linear programming rostering optimization model with the NN algorithm. It was found that the algorithm which was proposed granted more requests compared with the method which was followed by the airline. Wang et al. [23] designed a new "multivariable- weighted fusion" fire evaluation-based algorithm which is improved AHP so that the algorithm can detect the fire while simultaneously combining the variables and reduce the false alarm rate. To fuse the multiple variables for each sensor node, the paper developed an adaptive-weighted fusion method. It was found that the proposed algorithm can detect fire within 10 s, and the false alarm rate can be reduced.

3. Proposed Methodology

The technique of discovering and interpreting the underlying emotions depicted in textual data is known as sentiment analysis [24]. With the rapid growth of web 2.0 documents, research has been done on emotional issues, which are labeled by users as some emotions, such as surprise, sympathy, boredom, sadness, warmth, amusement, and anger. These sentiments can provide new capabilities for document classification. Textual information mining involves different strategies for information extraction, which may come from the rapid expansion of textual information, to access emotions expressed by facial expressions through human-machine interfaces. The issue of sentiment in text concerns the rapid growth of web 2.0 documents that give users a sense of responsibility for sentiment labels. As such, sentiment may take on a new quality for document classification [25].

3.1. Selection of Cockpit Samples. The Internet is mostly used as a method for collecting cockpit interior samples. For this purpose, models of currently operational commercial aircraft are first removed. Then, the ownership of these aircraft models is determined by the manufacturer. Finally, a dependable cockpit is chosen based on the information supplied by the manufacturers' image. The obtained cockpit samples must be screen and evaluated using the following fundamentals to assure the usefulness and validity of the experimental samples:

(i) The resolution of the experimental sample image should be good

(ii) Each component's elements in the test model are must be clear observable as feasible. There is no overlap or occlusion between component pieces, and they are fully displayed in the view of observers

(iii) The inside of the cockpit, including the windshield area, T-shaped region, cockpit entry area, top area, sidewall area, and ground area, should be included as much as feasible in the test model

(iv) The test model should include as many samples as feasible, with a low enough degree of similarity across models. It should be mentioned that just one representative model is chosen for each category upon the completion of the similarity survey

(v) The shooting angle is mainly placed towards the front to cover the T-shaped area in the cockpit

The previous five fundamental principle's major intention is to decrease the sound in the sample of exploratory. To develop the emotional sensation of the subject brought by the cockpit as well as make smaller the collision various angles on the finding outcome of the subjects in the next finding, the exploratory sample set and approximately perfect raw data are acquired. The important thing is, nowadays, there are hundreds of commercial airplanes running widespread so that the capacity of the current study will be efficiently decreased with the above-noticed process. So in this regard, the existent civil airplane models and kinds must be examined and screened. Next, statistical analysis must be carried out on the cockpit center of existent airplanes as well as features of the cockpit center of various kinds of airplanes, and their interaction with each other must be learned to acquire the product data of major makers. It must be expressed that the main passenger airplane creators, containing Airbus as well as Boeing, and the important business airplane makers, containing Bombardier, Dassault, and Embraer, are learned in this regard. This reliable information is used to search the cockpit image of the corresponding model. Additionally, the cockpit center exploratory sample database is improved by gathering images captured. At last, according to the circumstances of the image gathering, the images with blurred determination and obscure method features are ignored, and at last, 200 models are considered as a sample size. The round of screening is used to eliminate all high correspondence samples and decrease the size of samples from the 200 sample libraries. The leftover images are mentioned with the help of aerospace industrial specialists and aircraft design engineers. From the different people's feelings with various styles, the research software is implemented and then establishes their resemblances for deciding the shape of the cockpit. The resemblances within 2 sample images are received, and the similarity matrix is also designed from the research of samples similarities. The cluster analysis is employed for receiving 60 types of cockpit groups from the collected data. Each group chooses separate and representative sample pictures, and the above-mentioned 60 type samples also perform this operation.

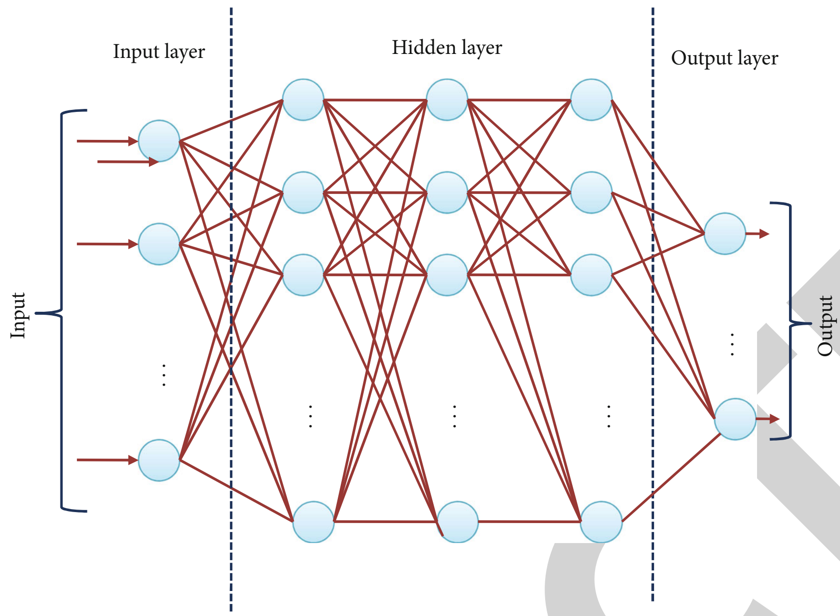

Figure 1: Artificial neural network (ANN).

First, we must clarify that the specialist has no comments against these samples, and that they have a similar opinion. Then the research sample was performed. Initially, the color saturation of images is modified for decreasing the power of color. So, the selection tools are used to pick suitable cockpit window frames and eliminate the messy background from the images. At last, the final effect eliminates all unwanted visual intervention factors. The result shows the image has possible angles and colors. The cockpit with enhanced performances provides a better emotional experience to the pilot and further enhances the comfort and pleasure while driving. Hence, it is necessary to provide a good performance cockpit. Therefore, this paper proposes a novel neural network based equilibrium optimization algorithm (NN-EOA) for cockpit emotion recognition. The steps involved in the proposed algorithm are depicted as follows.

3.2. Artificial Neural Network (ANN). An artificial neural network (ANN) is an information processing model used to record, store and utilize empirical data to simulate human brain function. Using the dataset, the network can understand the problem in detail and provide a complete strategy for dealing with nonlinear relationships and difficult challenges. Both input and output data are input and processed into this network as datasets, and then there is a pattern that shows the intrinsic relationship between the input and output. First, both the input and output data from the previous link are fed into the ANN model, and then the study data is loaded into the new ANN model for the new link. After this, the analytical data from the previous link as well as the input data from the new link are put into a new ANN model and the results are provided as the output parameters of the new link [26]. A schematic diagram of the artificial neural network is shown in Figure 1.

3.3. Equilibrium Optimization Algorithm (EOA). The EO algorithm is a metaheuristic algorithm inspired by the law of physics that is utilized to estimate the equilibrium states [27]. Like other optimization algorithms, the EO algorithm is commenced by initializing particle population. The below expression illustrates the population initialization process of the EO algorithm with n particles.

$$P_z^I = P_{\mathrm{Min}} + \mathfrak{R}_z (P_{\mathrm{Max}} - P_{\mathrm{Min}}), \quad z = 1, 2, 3, \cdots, n. \tag{1}$$

The term P_z^I represents the initial concentration of particle z, P_{Max} indicates maximum value of dimension, P_{Min} depicts minimum value of dimension, $n$implies total number of particles in the population, and $\mathfrak{R}_z$ signifies random number lies within the interval [0, 1]. In order to find the equilibrium states of the particle, each particle in the population is evaluated to determine the objective function [28]. Then, the concentration updating strategy is performed on the basis of equilibrium pool which consists of four optimal candidate particles and their arithmetic mean which is defined using the below equation.

$$P_{New} = P_r + \frac{g_R}{\gamma}(1-f) + (P - P_r)\cdot f. \tag{2}$$

From the above equation, P indicates current concentration vector of particle, P_r indicates random concentration vector of particle, generation rate is depicted as g_R, the exponential term is denoted as f, and the random vector is represented as γwhich is set as [0,1].

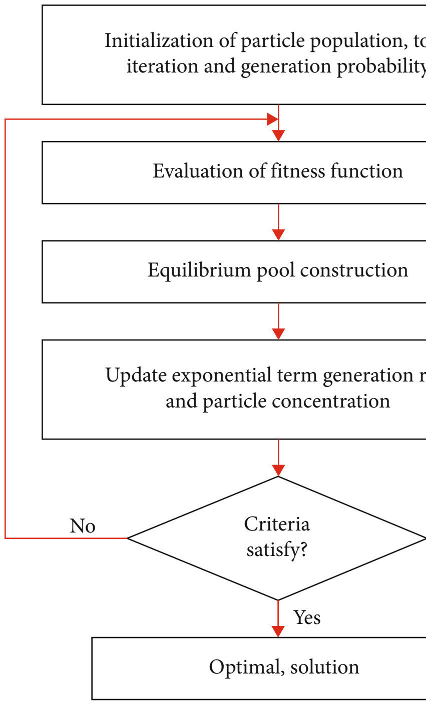

Figure 2: Flow chart of EOA.

Moreover, the generation rate g_R and exponential term f are calculated based on the following equations.

$$g_r = \begin{cases} 0.5R_1(P_r - \gamma P)f, & \text{if } R_2 \geq g_p, \\ 0, & \text{if } R_2 < g_p, \end{cases} \tag{3}$$
$$f = C_1 \operatorname{sign}(\lambda - 0.5) \cdot \left(e^{-\gamma(1-(t/t_{\text{Max}}))C_2(t/t_{\text{Max}})} - 1\right).$$

From the above two equations, R_1 and R_2 are the random numbers that range between 0 and 1, λ depicts the random vector which ranges between [0, 1], and the constants C_1 and C_2 are fixed as 2 and 1, respectively. Also, the generation probability g_R is set as 0.5; the terms t and t_{Max} depict current iteration and total iterations, respectively.

Then, each concentration vector of the particles is restored depending on the contribution of three parts in equation (2). The initial term illustrates the random concentration vector obtained from the construction of equilibrium pool. The last two terms look over the concentration differences and are accountable for accurate exploitation and exploration. Thus, EOA achieves optimal solutions from the search space effectively. The flowchart of the equilibrium optimization algorithm (EOA) is presented in Figure 2.

3.4. Improved Neural Network Algorithm-Based Cockpit Emotion Recognition. This section discusses IANN utilizing EO, and the performance of ANN is based on some retrieved parameters such as weight and bias that are determined by EO to enhance training. The ANN is a computational approach used to model the biological nervous systems. The most significant characteristic of ANN is the capability to "learn from experience" to improve the result. So the ANN is used in various applications such as control systems, pattern recognition, classification, detection, and image processing. The ANN training parameters may be improved by reducing the difference between intended and real outputs, and then, these parameters can be utilized to construct the network using EO. Here, each value of training parameters is treated as a resolution by the EO algorithm. The EO-ANN is used to evaluate the cockpit emotion in this paper.

The weights between input neuron as well as hidden layers in another neuron are denoted by x_{jk}, the bias is indicated by c_k, and the weight of the neuron in output and hidden layer is denoted by x_{k1}. The number of input data collected in the index is $k = 1, 2, .. \cdots n$, and the number of neurons in the hidden layer is $k = 1, 2, .. \cdots, o$; $o \times (n + 2) + 1$ denotes the bias and weight metrics utilized in the networks. After constructing the design of ANN, training by well-known input, and for finding the suitable biases and weights, the outputs are executed by utilizing EOA. The goal is to decrease the root mean square error (RMSE) function which is expressed as

$$\text{RMSE} = \sqrt{\frac{\sum_{S=0}^{O}(P_s - s_s)^2}{oe}}, \tag{4}$$

where P_s denotes the output related to s^{th} data points with the training sets through the network; the actual output is denoted by s_s, and the total number of data points in the dataset of training is represented by *oe*. Figure 3 depicts the proposed NN-based EOA architecture.

By using the proposed approach, the images for the interior cockpit design are evaluated for four emotional terminologies, namely, user-friendly (interactive), exact (precise), conventional (traditional), and tidy (neat).

4. Results and Discussions

Several performances of parameters are used for verifying the prediction performance in distinct designs. To evaluate the results, there are no common standards used. Generally, the adopted error index consists of three types, and they are mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE).

4.1. Mean Absolute Error (MAE). It is defined as the measurement of errors between the paired observations to express the equal phenomenon.

$$\text{MAE} = \frac{1}{M}\sum_{u=1}^{M}\left|z_u - \widehat{z_u}\right|, \tag{5}$$

where the total number of cockpits is denoted by M, the forecasted emotional evaluation data is represented by $\widehat{z}_u$, and the raw emotional evaluation data is indicated by z_u.

4.2. Mean Absolute Percentage Error (MAPE). It is also called mean absolute percentage deviation, and it is defined as the measure of predicting the accuracy in forecasting algorithm in the statics.

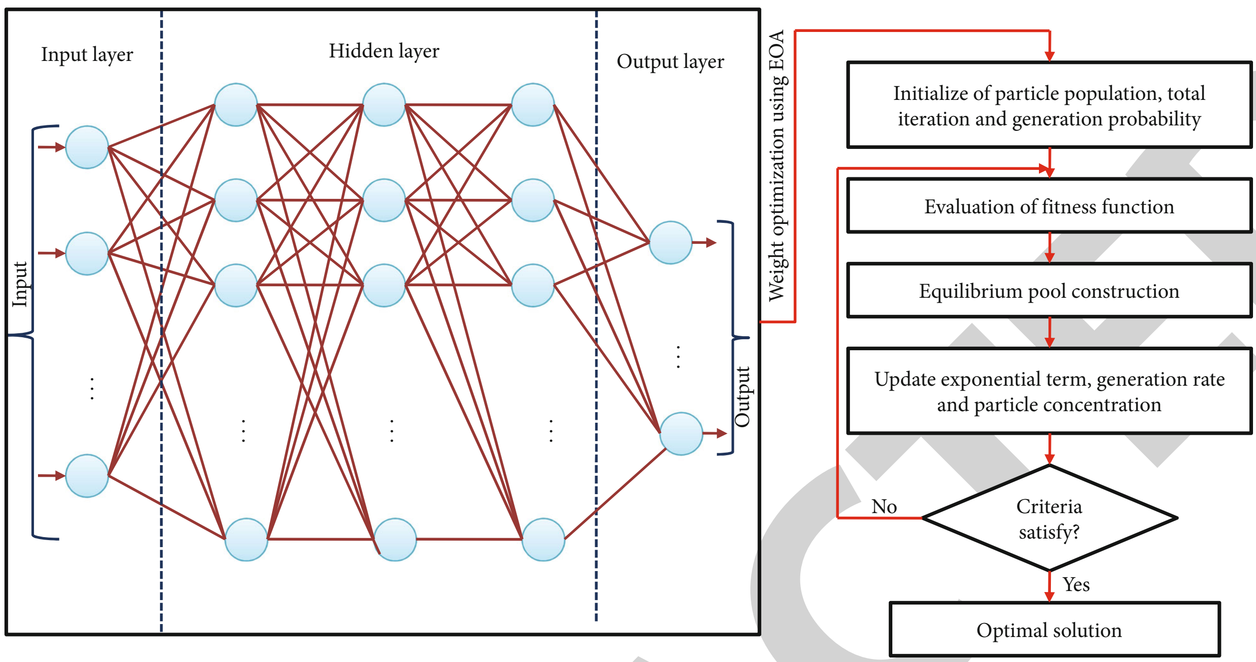

Figure 3: Proposed NN-EOA algorithm.

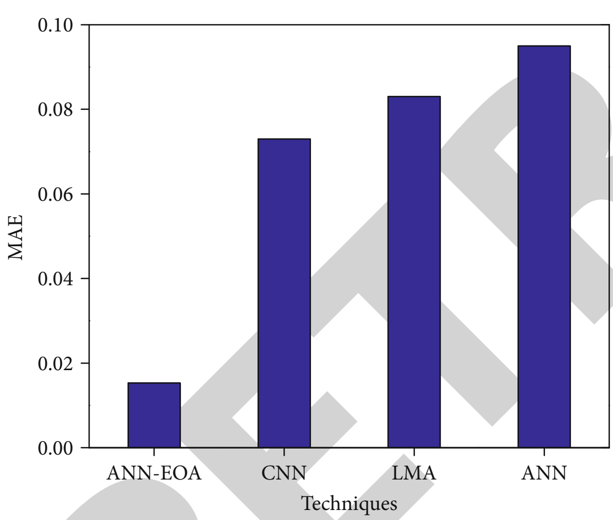

Figure 4: Comparative analysis of MAE.

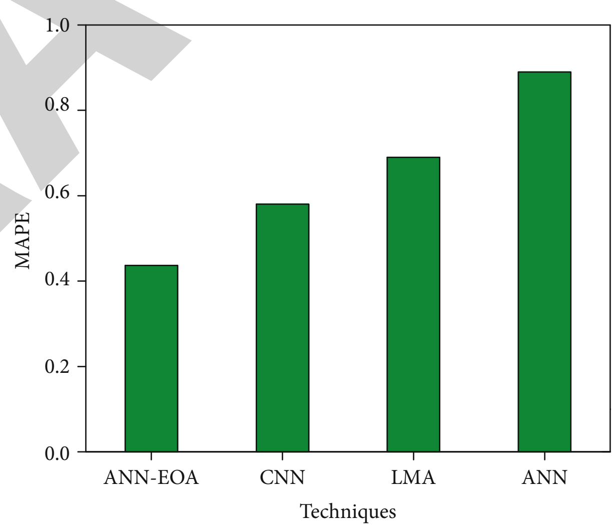

Figure 5: Comparative analysis of MAPE.

$$\mathrm{MAPE} = \frac{1}{M}\sum_{u=1}^{M}\left|\frac{z_u - \widehat{z_u}}{z_u}\right| \times 100\%. \quad (6)$$

4.3. Root Mean Squared Error (RMSE). It is defined as the standard variation of the residual and utilized to measure the difference among values is computed through an estimator.

$$\mathrm{RMSE} = \sqrt{\frac{1}{M}\sum_{u=1}^{M}\left(z_u - \widehat{z_u}\right)^2}. \quad (7)$$

Figure 4 represents the comparative analysis of ANN-EOA with different techniques. The proposed artificial neural network-equilibrium optimization algorithm (ANN-EOA) technique was compared with convolutional neural network (CNN), Levenberg Marquardt Algorithm (LMA), and artificial neural network (ANN), respectively. In the figure, different techniques are plotted with respect to mean absolute error (MAE), and it shows that the MAE rate of ANN-EOA is about 0.0153 which is lower than other techniques. The mean absolute percentage error (MAPE) of different techniques is compared, and their values are graphically represented in Figure 5. The MAPE values of different techniques like ANN-EOA, CNN, LMA, and ANN are determined and compared with each other. However, ANN-EOA has a lower MAPE rate of 0.4367 and the other three methods have a higher MAPE rate

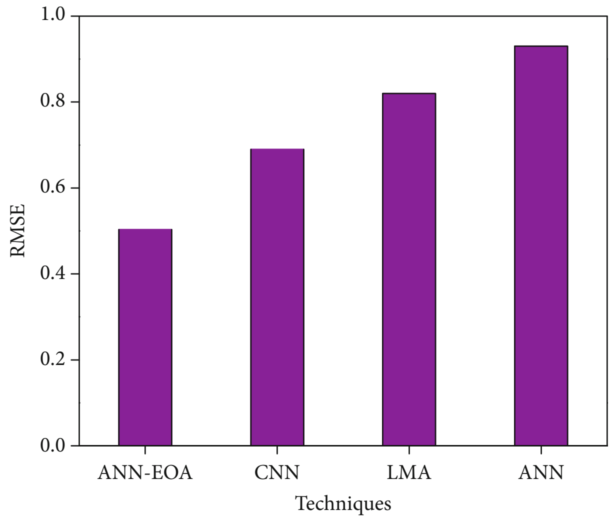

Figure 6: Comparative analysis of RMSE.

Table 1: Explanation of Cronbach's alpha values.

Coefficient of Cronbach's alpha	Reliability level of internal consistency
More than 0.90	Excellent
0.80-0.89	Good
0.70-0.79	Acceptable
0.6-.69	Questionable
0.5-0.59	Poor
Less than 0.59	Unacceptable

Table 2: Scoring-based sentiment expressed.

Assessment score	Emotional fit
1	Not at all suitable
2	Not suitable
3	Generally suitable
4	Suitable
5	Completely suitable

whereas ANN has a higher MAPE rate. Figure 6 depicts the comparative analysis of root mean square error (RMSE) of ANN-EOA with CNN, LMA, and ANN existing techniques. Here, the RMSE value of each technique is compared and expressed in the figure. As a result, the RMSE value of ANN-EOA is smaller compared to other techniques, and the achieved RMSE value is 0.5031 and the artificial neural network has attained a larger RMSE value.

Cronbach's alpha is the measure of internal consistency. The reliability analysis is measured based on Cronbach's alpha value. The general rule of Cronbach's alpha is that a reliability coefficient of 0.70 or above is regarded as "acceptable" in the research context. Table 1 shows the explanation of Cronbach's alpha values.

Using the five-level semantic scale method based on the research samples and image language, a fifth-order SD questionnaire is established that is based on cockpit modeling image. The data for evaluation is filled by the investigator into the grid. The score is given for each sample of research under the four image words. The evaluation method of scoring principle assessment is presented in Table 2.

5. Conclusion

Identifying essential resources for powerful and secure cooperation in the cockpit as well as making them into guiding schedule is the research in recent years. Various researches express that the neural network is the right method for emotional analysis and linguistic consideration. Therefore, this paper proposes a novel neural network-based equilibrium optimization algorithm (NN-EOA) for cockpit emotion recognition with high accuracy and minimizes the error rate during evaluation. Mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) rate of ANN-EOA with different existing techniques like CNN, LMA, and ANN are compared, and it was determined that the values of MAE, MAPE, and RMSE are lower for the proposed ANN-EOA technique. In the future, hybrid metaheuristic algorithms will be proposed to enhance the efficiency of the system.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that no conflict of interest is associated with this study.

Authors' Contributions

This study was done by the authors named in this article, and the authors accept all liabilities resulting from claims which relate to this article and its contents.

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